One decade of biomedical problems using ICA: a full comparative study

L. Albera[1], A. Kachenoura[1], A. Karfoul[1], P. Comon[2] and L. Senhadji[1]

[1] INSERM, U642, Rennes, F-35000, France
Universit de Rennes 1, LTSI, Rennes, F-35000, France
[2] CNRS, U6070, Sophia-Antipolis, F-06903, France
Universit de Nice Sophia-Antipolis, I3S, Nice Sophia-Antipolis, F-06903, France

Abstract— **This communication aims at giving some insights into the use of Independent Component Analysis (ICA) for solving biomedical problems. First the concept of ICA is reviewed and different classes of ICA methods are described. Next a survey on most encountered biomedical problems solved using ICA is detailed. Finally a comparative performance study of thirteen ICA algorithms is performed on biomedical signals.**

Keywords— **Independent Component Analysis (ICA), biomedical applications, comparative study.**

I. WHAT IS ICA?

Given one realization of a N-dimensional random vector process whose m-th vector is defined by:

$$x[m] = As[m] + n[m] \tag{1}$$

where $s[m]$ is a P-dimensional source vector with statistically independent components, $\nu[m]$ is a noise vector which is independent from the source vector and A is the so-called *mixing matrix*. The ICA problem consists in finding, only from the data, a $(N \times P)$ matrix W, called *separator*, such that:

$$y[m] = W^{\mathsf{T}} x[m] \tag{2}$$

is an estimate of $s[m]$ to within a diagonal matrix and a permutation. But how to use the statistical independence of the source components in order to restore them?

Entropy and mutual information. A natural way to measure statistical dependence consists in using the *Mutual Information* (MI) [6], wich can be easily related to the (Shannon) Differential Entropy (DE) or its normalized version called *negentropy*. The INFOMAX method solves the ICA problem by maximizing an output DE using the natural gradient algorithm [6]. The PICA [8] algorithm uses the parametric Pearson model in the minimization of the MI. The FastICA technique extracts each source by maximizing an approximation of the negentropy by means of an approximate Newton iteration. Another way to measure statistical dependence, less natural but easier to compute consists in using cumulants.

Cumulants. The r-th order cumulants are the coefficients of the Taylor expansion of the second characteristic function about the origin. They enjoy very attractive properties such that i) if at least two components or groups of components are statistically independent, then all cumulants involving these components are null, ii) if a variable is Gaussian, then its HO marginal cumulant is null, iii) cumulants are symmetric arrays, say the value of their entries does not change by permutation of their indices and iv) cumulants satisfy the multi-linearity property. The SOBI [6], TFBSS [5] and SOBIUM [9] techniques jointly diagonalize a set of Second Order (SO) cumulant matrices built from the data while COM2 [6], STOTD [10] and JADE [6] diagonalize in different ways a Fourth Order (FO) cumulant matrix computed from the data. The ALS-FUBI$_{\mathrm{ACDC}}$ algorithm diagonalises a set of FO cumulant matrices calculated from the data, as FOBIUM, but using a non-orthogonal diagonalization scheme. Eventually, the ELScaf [3] use *pseudo-cumulants* of the data defined as the derivatives of the second characteristic function in points different form the origin.

II. A BIBLIOGRAPHICAL SURVEY ON BIOMEDICAL APPLICATIONS

In the last decade, ICA-based methods have been widely used in the field of biomedical engineering, especially to analyze electrophysiological signals.

A. Functional brain imaging

Promising results have been reported in electroencephalographical signal processing using ICA techniques. They include Evoked Potentials (EP) enhancement, categorized brain signals detection, spindles detection and estimation, and artifacts reduction. The analysis of two particular neurophysiological signals is investigated in this context.

P-300 evoked potentials. P-300 is a positive ERP, which occurs over the parietal cortex with a latency of about 300 ms after rare or task-relevant stimuli. The P-300 can be obtained in all stimulus modalities (auditory as well as visual and somatosensory modalities) and can even be produced by the omission of a stimulus in a regular train of stimuli [11]. Due to the poor SNR as well as to the presence of artifacts (such as ocular, muscular and cardiac activities), the P-300 wave can be buried in the signal collection. Hence, the main objective when applying ICA to P-300-based BCI systems is two-fold: i) to denoise the EEG signal in order to enhance the SNR of the P-300 and ii) to separate ERP responses to target and non-target ones. The first point was considered by Bayliss and al. in [1]. Authors described an experiment demonstrating the existence of a P-300 wave when facing red stoplights and the absence of this signal when facing yellow stoplights in a virtual driving environment. Bayliss et al. pointed out that most of artifacts were due to eye movements. They showed that an ICA technique was able to separate the background EEG signal and eye movements from the P-300 signal. In [14], Xu et al. dealt with the second point and proposed to enhance the P-300 wave detection in the P-300 speller paradigm used to record the database IIb of BCI Competition 2003 [2]. As classical methods for enhancing the detection of P-300 components are time consuming, authors proposed to use an ICA technique in the training phase. The key issue of this study is the selection of the meaningful Independent Components (ICs). Indeed, according to the prior physiological knowledge, authors proposed two additional post-processing steps, namely the temporal manipulation of ICs and the spatial manipulation of ICs (see [14, section II] for details). They showed that the proposed algorithm for P-300 detection based on ICA provided a perfect accuracy (100%) in the competition.

Mu rhythm and other activities from sensorimotor cortex. EEG contains a fairly wide frequency spectrum. Nevertheless, the relevant frequency range from the psychophysiological viewpoint lies between 0.1 Hz and 100 Hz [11]. For example, *Beta* rhythm is associated with active thinking and attention whereas the *Mu* rhythm is affected by movements or movement imagery. QIN et al. [12] present a pilot study aimed at classifying motor imagery, using ICA as a spatio-temporal filter. More precisely, the study was focused on the *Mu* rhythm which decreases or desynchronizes with movement or movement imagery. Authors conduct an experiment where the subject was asked to imagine right or left-hand movement according to a timetable. EEG were recorded using 59 electrodes but only those located around sensorimotor cortex were used in the study. ICA was used to extract ICs related to the left and the right motor imagery task. The obtained results show that ICA plays an important role in extracting a useful feature that identifies the imagined hand movement. A promising classification rate (about 80 %) of left or right-hand movement imagery was obtained on human subject studies, based only on a single trial and without any training procedure.

B. Electrocardiogram signal analysis

The electrocardiogram (ECG) reflects the electrical activity of the heart which is usually recorded with surface electrodes placed on the chest, arms and limbs. Although the ECG recording techniques are very effective, the distortions caused by noises and interfering physiological signals are still very important. Let us consider in more details the two following classical applications.

Noninvasive fetal ECG extraction. The FECG contains a lot of useful information which can provide valuable clinical indication about the fetal well-being and then allow for an early diagnosis of fetal cardiac abnormalities and other pathologies. One of the challenging tasks is to reliably detect and enhance FECG in a non-invasive fashion by using several skin electrodes located on a pregnant woman's body. In fact, the obtained ECG also contains the Mother ECG (MECG), and other interfering signals including the respiration, the ElectroMyoGram (EMG), the electrodes movements, etc. De Lathauwer et al. [4] show that the ECG data recorded from mother's skin electrodes can be modeled as a linear static mixture of independent sources. Indeed, The transfer function between the bioelectric sources to body surface electrodes is assumed to be linear, resistive and the hight propagation velocity of the electrical signal in the human tissues validates the instantaneous assumption of the model. Besides, the authors state in accordance with that the MECG-subspace is characterized by a three-dimensional vector signal, whereas the dimension of FECG-subspace is subject to changes during the pregnancy period. Applying the COM2 ICA method to eight mother surface lead ECG, the authors show that the full three-dimension MECG subspace is well reconstructed whereas the FECG subspace is extracted in two different components.

Atrial activity extraction for atrial fibrillation. Atrial Fibrillation (AF) is associated with increased mortality and hospitalization for most people, and understanding of pathological mechanisms underlying AF using non-invasive diagnosis tools such as surface ECG is crucial to improve the patients treatment strategies. However, due to the low Signal to Noise Ratio (SNR) of the Atrial Activity (AA) on the surface 12-lead ECG, the analysis of AF episode remains difficult. The AF problem was tackled by means of ICA methods in [13]. The authors justify, on the one hand, three basic considerations about the AA and the Ventricular Activity (VA) and, on the other hand, the fashion which both activities are recorded from the surface electrodes: i) the independence between VA and AA, ii) the sub-Gaussian and super-Gaussian distributions of AA and VA, respectively and iii) the linear static mixing model followed by the data. The authors applied the FastICA algorithm on the 12-lead ECG of seven patients suffering from AF. The obtained results show that three separated sources have a more sub-Gaussian distribution and hence are candidates to be related to AA. Four sources are associated with Gaussian noise and artifact, whereas five extracted components which present a super-Gaussian distribution contain a VA. One important problem that arises when ICA is used in biomedical context is to automatically select and classify independent source of interest. Typically, in the above example the question is: how to choose the most informative AA source among the three extracted components with a sub-Gaussian distribution? The authors solve this problem by exploiting some prior information about spectral content of AA during AF episode. Indeed, the AA signal exhibits a narrowband spectrum with a main frequency of between $3.5-9Hz$. Thus, they apply a spectral analysis over all the sources with sub-Gaussian distribution and choose the component which presents a major peak at frequency $f = 6.31Hz$, as the AA source.

III. Performance comparison of thirteen ICA methods

Performance criterion. In order to quantitatively compare several ICA methods, we used the Signal to Interference-plus-Noise Ratio (SINR) of each source after separation as performance criterion [6]. More precisely, the SINR of the p-th source at the i-th output of the separator $W = [w_1, \ldots, w_P]$ is defined by:

$$\mathrm{SINR}_p[w_i] = \pi_p |{w_i}^\top a_p|^2 / ({w_i}^\top R_{v_p} w_i) \qquad (3)$$

where π_p represents the power of the p-th source, w_i the i-th column of the separator W and R_{v_p} is the total noise covariance matrix for the p-th

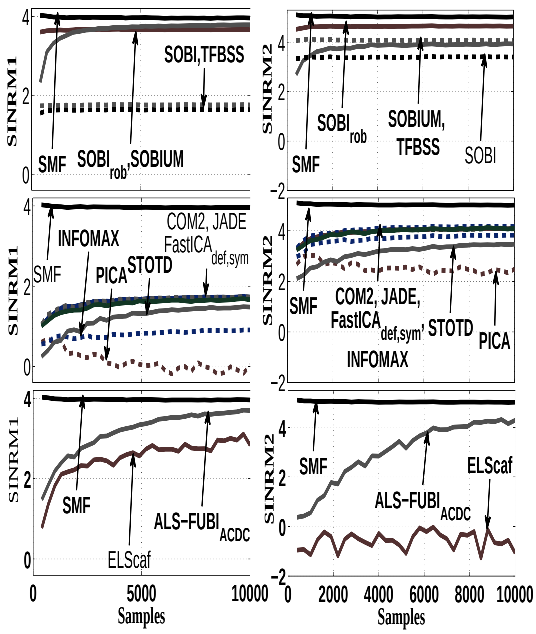

Fig. 1: Criterion SINRM as a function of data samples for $N = 7$ surface electrodes and $P = 2$ sources and with a SNR of 5dB.

source, corresponding to the estimated data covariance matrix in the absence of the component p. On the basis of these definitions, the restitution quality of the p-th source at the output of the separator W is evaluated by computing the maximum of $\mathrm{SINR}_p[w_i]$ with respect to i for $1 \leq i \leq P$. This quantity is denoted by SINRM_p. The performance of a source separator W is defined by the line vector $\mathrm{SINRM}(W) = (\mathrm{SINRM}_1[W], \ldots, \mathrm{SINRM}_P[W])$. In a given context, a separator $W^{(1)}$ is better than another one $W^{(2)}$ for retrieving the source p, provided that $\mathrm{SINRM}_p[W^{(1)}] > \mathrm{SINRM}_p[W^{(2)}]$.

Data generation. We consider the case of the extraction of the Mu rhythm presented in section A. when seven surface electrodes, located around the sensorimotor cortex, are used to record EEG data. In such a context the surface observations can be considered as a noisy mixture of one source of interest, namely the Mu signal, and artifact sources such as an ocular. The intracerebral Mu wave located in the motor cortex is simulated using the parametric model of Jansen [7] whose parameters are selected to derive a Mu-like activity. The ocular signal is issued from our polysommnographic database. As far as the additive noise is considered, it is modeled as the sum of instrumental and physiological noises. Therefore, a Gaussian vector process is used to simulate the instrumental noise while a brain volume conduction of 800 independent EEG sources, generated using the Jansen model, is simulated to produce a surface background EEG activity. Finally the mixing matrix is defined as the concatenation of two columns modeling the head volume conduction of the Mu rythm and the ocular activity toward the surface.

Computer results. The SINRM of each source at the output of SOBI, SOBI_{rob} (a SOBI modified version based on a robust whitening procedure), SOBIUM, TFBSS, PICA, INFOMAX, STOTD, COM2, JADE, FastICA ($\text{FastICA}_{\text{def}}$ and $\text{FastICA}_{\text{sym}}$, the deflation and symmetric versions, respectively), $\text{ALS-FUBI}_{\text{ACDC}}$ and ELScaf was computed as a function of the number of samples (with a sampling rate of 256 Hz) and for a SNR of 5dB. Considering the ocular activity's extraction (i.e. SINRM_1 in the left column), we note a higher performance of SOBI_{rob}, $\text{ALS-FUBI}_{\text{ACDC}}$ and SOBIUM (i.e. -0.5dB with respect to the optimal separator (SMF)). Regarding the other algorithms, their performance is still reasonable (i.e. -2dB from SMF) except for INFOMAX and PICA which separators seem to be biased in this context. As far as the Mu wave's extraction is concerned (i.e. SINRM_2 in the right column), we observe the very good behavior of the SOBI_{rob} method with respect the other ones. This is due to the fact that SOBI_{rob} is not affected by the spatially correlated noise. The ALScaf algorithm fails in the extraction of the Mu wave whereas $\text{ALS-FUBI}_{\text{ACDC}}$ requires a large amount of samples to converge. The quasi-Gaussian distribution of the Mu wave may explain such a behavior. In the case of the ALScaf method, the use of more grid points or the exploitation of several HO derivatives should improve its performance. The STOTD, SOBI, COM2, JADE, TFBSS, SOBIUM, INFOMAX, $\text{FastICA}_{\text{sym}}$ and $\text{FastICA}_{\text{def}}$ globally give acceptable results (i.e. -1.5dB from the SMF). Note that the PICA algorithm provides poor separation of the Mu source.

IV. CONCLUSION

The concept of ICA is briefly reviewed in this paper allowing to cover a wide range of techniques. In addition, ICA for biomedical engineering is tackled by giving a survey on its widespread applications. A comparative performance analysis on electrophysiological data reproducing the real scalp EEG recordings is conducted. The obtained results show that the performance of the ICA algorithms depend on the electrophysiological nature of the sources that is extracted. Hence, the collection and the exploitation of statistical and physiological information on the sources of interest, such as temporal color or distribution (Gaussian or not), can help to choose the more appropriate ICA method. In our study context, the SOBI_{rob} method gives the best results probably due to the source temporal non-whiteness and the noise temporal whiteness.

ACKNOWLEDGEMENTS

This work is supported in part by the French Government under two ANR Contracts, namely DECOTES (06-BLAN-0074) and mv-EMD (BLAN07-0314-02).

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